

CLAIM AMENDMENTS

Please amend claims 1, 3, 5, 7-8, 11-38, 40 and 60-61 to read as follows. Please cancel claims 2, 4, 6, 39, 41 and 43. All other claims are unamended.

1. (currently amended) A method for automating the identification of meaningful features and the formulation of expert rules for classifying magnetocardiography data, comprising—
~~the step of:~~

applying a ~~kernel~~-wavelet transform to sensed data acquired from sensors sensing ~~electromagnetic~~ fields generated by a patient's heart activity, resulting in ~~transformed~~-wavelet domain data;

applying a kernel transform to said wavelet domain data, resulting in transformed data; and, prior to

identifying said meaningful features and formulating said expert rules from classifying said transformed data, using machine learning.

2. (cancelled)

3. (currently amended) The method of claim 1, ~~for classifying magnetocardiography data~~, further comprising ~~the step of:~~

acquiring said sensed data from magnetic sensors proximate a patient's heart.

4. (cancelled)

5. (currently amended) The method of claim 1, further

2 | ~~comprising the step of:~~
3 | classifying said transformed data using machine learning.

1 | 6. (cancelled)

1 | 7. (currently amended) The method of claim 3, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using machine learning.

1 | 8. (currently amended) The method of claim 4, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using machine learning.

1 | 9. (original) The method of claim 1, said kernel transform
2 | satisfying Mercer conditions.

1 | 10. (original) The method of claim 1, said kernel transform
2 | comprising a radial basis function.

1 | 11. (currently amended) The method of claim 1, ~~said step of~~
2 | ~~applying a kernel transform comprising the steps of:~~
3 | assigning said transformed data to a first hidden layer of a
4 | neural network;
5 | applying training data descriptors as weights of said first
6 | hidden layer of said neural network; and
7 | calculating weights of a second hidden layer of said neural
8 | network numerically.

1 | 12. (currently amended) The method of claim 11, ~~said step of~~
2 | calculating said weights of said second hidden layer numerically
3 | ~~further comprising the step of:~~
4 | calculating said weights of said second hidden layer using

5 kernel ridge regression.

1 | 13. (currently amended) The method of claim 1, ~~said step of~~
2 | ~~applying a kernel transform comprising the step of:~~
3 | applying a direct kernel transform.

1 14. (currently amended) The method of claim 1, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using a self-organizing map
4 | (SOM).

1 15. (currently amended) The method of claim 1, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using a direct kernel self-
4 | organizing map (DK-SOM).

1 16. (currently amended) The method of claim 1, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using kernel partial least
4 | square (K-PLS) machine learning.

1 17. (currently amended) The method of claim 1, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using direct kernel partial
4 | least square (DK-PLS) machine learning.

1 18. (currently amended) The method of claim 1, further
2 | ~~comprising the step of:~~
3 | classifying said transformed data using a least-squares
4 | support vector machine (LS-SVM).

1 19. (currently amended) The method of claim 1, further

2 | ~~comprising the step of:~~

3 | classifying said transformed data using a direct kernel

4 | principal component analysis (DK-PCA).

1 | 20. (currently amended) The method of claim 1, further

2 | ~~comprising the step of:~~

3 | classifying said transformed data using a support vector

4 | machine (SVM / SVMlib).

1 | 21. (currently amended) The method of claim 20, ~~said step of~~

2 | classifying said transformed data using a support vector machine

3 | (SVM / SVMlib) further ~~comprising the step of:~~

4 | setting an SVMlib regularization parameter, C, to $C=1/\lambda$, for

5 | an n data kernel, wherein:

6 | said λ is proportional to said n to a power of $3/2$

1 | 22. (currently amended) The method of claim 20, ~~said step of~~

2 | classifying said transformed data using a support vector machine

3 | (SVM / SVMlib) further ~~comprising the step of:~~

4 | setting an SVMlib regularization parameter, C, to $C=1/\lambda$, for

5 | an n data kernel, wherein:

$$6 | \lambda = \min \left\{ 1; \left(\frac{n}{1500} \right)^{\frac{3}{2}} \right\} .$$

1 | 23. (currently amended) The method of claim 12, ~~said step of~~

2 | ~~converting transforming~~ said sensed data into a said wavelet

3 | domain data ~~comprising the step of:~~

4 | applying a Daubechies wavelet transform to said sensed data.

1 24. (currently amended) The method of claim 12, further
2 comprising ~~the step of:~~

3 selecting features from said wavelet domain data which
4 improve said classification of magnetocardiography data.

1 25. (currently amended) The method of claim 24, ~~said step of~~
2 selecting said features further comprising ~~the step of:~~

3 eliminating selected undesirable features from said wavelet
4 data.

1 26. (currently amended) The method of claim 25, ~~said step of~~
2 eliminating selected undesirable features comprising ~~the step of:~~

3 eliminating outlying data from said wavelet data.

1 27. (currently amended) The method of claim 25, ~~said step of~~
2 eliminating selected undesirable features comprising ~~the step of:~~

3 eliminating cousin descriptors from said wavelet data.

1 28. (currently amended) The method of claim 24, ~~said step of~~
2 selecting said features further comprising ~~the step of:~~

3 retaining only selected desirable features from said wavelet
4 data.

1 29. (currently amended) The method of claim 28, ~~said step of~~
2 retaining only selected desirable features further comprising ~~the~~
3 ~~steps of:~~

4 using a training data set; and

5 using a validation data set for confirming an absence of
6 over-training of said training set.

1 30. (currently amended) The method of claim 29, ~~said step of~~

2 | retaining only selected desirable features further comprising ~~the~~
3 | ~~steps of:~~

4 | using a genetic algorithm to obtain an optimal subset of
5 | features from said training data set; and
6 | using said genetic algorithm for evaluating performance on
7 | said validation data set.

1 | 31. (currently amended) The method of claim 29, ~~said step of~~
2 | retaining only selected desirable features further comprising ~~the~~
3 | ~~steps of:~~

4 | measuring sensitivities of said features from said wavelet
5 | data in relation to a predicted responses of said features; and
6 | eliminating lower-sensitivity features from among said
7 | features with comparatively lower sensitivity than other, higher-
8 | sensitivity features from among said features.

1 | 32. (currently amended) The method of claim 24, ~~said step of~~
2 | selecting said features further comprising ~~the steps of:~~

3 | eliminating selected undesirable features from said wavelet
4 | data; and

5 | retaining only selected desirable features from said wavelet
6 | data.

1 | 33. (currently amended) The method of claim 1, further
2 | comprising ~~the step of:~~

3 | normalizing said sensed data.

1 | 34. (currently amended) The method of claim 33, ~~said step of~~
2 | normalizing said sensed data comprising ~~the step of:~~

3 Mahalanobis scaling said sensed data.

1 35. (currently amended) The method of claim 1, further

2 comprising ~~the step of~~:

3 centering a kernel of said kernel transform.

1 36. (currently amended) The method of claim 35, ~~said step of~~

2 centering said kernel comprising ~~the steps of~~:

3 subtracting a column average from each column of a training
4 data kernel;

5 storing said column average for later recall, when centering
6 a test data kernel.

7 subtracting a row average from each row of said training data
8 kernel.

1 37. (currently amended) The method of claim 36, ~~said step of~~

2 centering said kernel further comprising ~~the steps of~~:

3 adding said stored column average to each column of said test
4 data kernel;

5 for each row, calculating an average of said test data
6 kernel; and

7 subtracting said row average from each horizontal entry of
8 said test data kernel.

1 38. (currently amended) An apparatus for automating the

2 identification of meaningful features and the formulation of

3 expert rules for classifying magnetocardiography data, comprising

4 computerized storage, processing and programming for:

5 applying a ~~kernel~~ wavelet transform to sensed data acquired

6 from sensors sensing ~~electromagnetic~~ fields generated by a
 7 patient's heart activity, resulting in ~~transformed~~ wavelet domain
 8 data;
 9 applying a kernel transform to said wavelet domain data,
 10 resulting in transformed data; and, ~~prior to~~
 11 identifying said meaningful features and formulating said
 12 expert rules from ~~classifying~~ said transformed data, using machine
 13 learning.

1 39. (cancelled)

1 40. (currently amended) The apparatus of claim 38, ~~for~~
 2 ~~classifying magneto-cardiography data,~~ further comprising an input
 3 for:

4 acquiring said sensed data from magnetic sensors proximate a
 5 patient's heart.

1 41. (cancelled)

1 42. (original) The apparatus of claim 38, further comprising
 2 computerized storage, processing and programming for:

3 classifying said transformed data using machine learning.

1 43. (cancelled)

1 44. (original) The apparatus of claim 40, further comprising
 2 computerized storage, processing and programming for:

3 classifying said transformed data using machine learning.

1 45. (original) The apparatus of claim 41, further comprising
 2 computerized storage, processing and programming for:

3 classifying said transformed data using machine learning.

1 46. (original) The apparatus of claim 38, wherein kernel
2 transform satisfies Mercer conditions.

1 47. (original) The apparatus of claim 38, said kernel transform
2 comprising a radial basis function.

1 48. (original) The apparatus of claim 38, said computerized
2 storage, processing and programming for applying a kernel
3 transform further comprising computerized storage, processing and
4 programming for:

5 assigning said transformed data to a first hidden layer of a
6 neural network;

7 applying training data descriptors as weights of said first
8 hidden layer of said neural network; and

9 calculating weights of a second hidden layer of said neural
10 network numerically.

1 49. (original) The apparatus of claim 48, said computerized
2 storage, processing and programming for calculating said weights
3 of said second hidden layer numerically further comprising
4 computerized storage, processing and programming for:

5 calculating said weights of said second hidden layer using
6 kernel ridge regression.

1 50. (original) The apparatus of claim 38, said computerized
2 storage, processing and programming for applying a kernel
3 transform further comprising computerized storage, processing and
4 programming for:

5 applying a direct kernel transform.

1 51. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:
3 classifying said transformed data using a self-organizing map
4 (SOM).

1 52. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:
3 classifying said transformed data using a direct kernel self-
4 organizing map (DK-SOM).

1 53. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:
3 classifying said transformed data using kernel partial least
4 square (K-PLS) machine learning.

1 54. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:
3 classifying said transformed data using direct kernel partial
4 least square (DK-PLS) machine learning.

1 55. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:
3 classifying said transformed data using a least-squares
4 support vector machine (LS-SVM).

1 56. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:
3 classifying said transformed data using a direct kernel
4 principal component analysis (DK-PCA).

1 57. (original) The apparatus of claim 38, further comprising

2 computerized storage, processing and programming for:
 3 classifying said transformed data using a support vector
 4 machine (SVM / SVMlib).

1 58. (original) The apparatus of claim 57, said computerized
 2 storage, processing and programming for classifying said
 3 transformed data using a support vector machine (SVM / SVMlib)
 4 transform further comprising computerized storage, processing and
 5 programming for:

6 setting an SVMlib regularization parameter, C , to $C=1/\lambda$, for
 7 an n data kernel, wherein:

8 said λ is proportional to said n to a power of $3/2$

1 59. (original) The apparatus of claim 57, said computerized
 2 storage, processing and programming for classifying said
 3 transformed data using a support vector machine (SVM / SVMlib)
 4 transform further comprising computerized storage, processing and
 5 programming for:

6 setting an SVMlib regularization parameter, C , to $C=1/\lambda$, for
 7 an n data kernel, wherein:

$$8 \quad \lambda = \min \left\{ 1; \left(\frac{n}{1500} \right)^{\frac{3}{2}} \right\}.$$

1 60. (original) The apparatus of claim 38~~39~~, said computerized
 2 storage, processing and programming for ~~converting~~transforming
 3 said sensed data into ~~a~~a said wavelet domain data comprising
 4 computerized storage, processing and programming for:

5 applying a Daubechies wavelet transform to said sensed data.

1 | 61. (currently amended) The apparatus of claim 38~~39~~, further
2 | computerized storage, processing and programming for:

3 | selecting features from said wavelet domain data which
4 | improve said classification of magnetocardiography data.

1 | 62. (original) The apparatus of claim 61, said comprising
2 | computerized storage, processing and programming for selecting
3 | said features further comprising computerized storage, processing
4 | and programming for:

5 | eliminating selected undesirable features from said wavelet
6 | data.

1 | 63. (original) The apparatus of claim 62, said comprising
2 | computerized storage, processing and programming for eliminating
3 | selected undesirable features comprising computerized storage,
4 | processing and programming for:

5 | eliminating outlying data from said wavelet data.

1 | 64. (original) The apparatus of claim 62, said computerized
2 | storage, processing and programming for eliminating selected
3 | undesirable features comprising computerized storage, processing
4 | and programming for:

5 | eliminating cousin descriptors from said wavelet data.

1 | 65. (original) The apparatus of claim 61, said computerized
2 | storage, processing and programming for selecting said features
3 | further comprising computerized storage, processing and
4 | programming for:

5 retaining only selected desirable features from said wavelet
6 data.

1 66. (original) The apparatus of claim 65, said computerized
2 storage, processing and programming for retaining only selected
3 desirable features further comprising computerized storage,
4 processing and programming for:

5 using a training data set; and

6 using a validation data set for confirming an absence of
7 over-training of said training set.

1 67. (original) The apparatus of claim 66, said computerized
2 storage, processing and programming for retaining only selected
3 desirable features further comprising computerized storage,
4 processing and programming for:

5 using a genetic algorithm to obtain an optimal subset of
6 features from said training data set; and

7 using said genetic algorithm for evaluating performance on
8 said validation data set.

1 68. (original) The apparatus of claim 66, said computerized
2 storage, processing and programming for retaining only selected
3 desirable features further comprising computerized storage,
4 processing and programming for:

5 measuring sensitivities of said features from said wavelet
6 data in relation to a predicted responses of said features; and

7 eliminating lower-sensitivity features from among said
8 features with comparatively lower sensitivity than other, higher-

9 sensitivity features from among said features.

1 69. (original) The apparatus of claim 61, said computerized
2 storage, processing and programming for selecting said features
3 further comprising computerized storage, processing and
4 programming for:

5 eliminating selected undesirable features from said wavelet
6 data; and

7 retaining only selected desirable features from said wavelet
8 data.

1 70. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:

3 normalizing said sensed data.

1 71. (original) The apparatus of claim 70, said computerized
2 storage, processing and programming for normalizing said sensed
3 data comprising computerized storage, processing and programming
4 for:

5 Mahalanobis scaling said sensed data.

1 72. (original) The apparatus of claim 38, further comprising
2 computerized storage, processing and programming for:

3 centering a kernel of said kernel transform.

1 73. (original) The apparatus of claim 72, said computerized
2 storage, processing and programming for centering said kernel
3 comprising computerized storage, processing and programming for:

4 subtracting a column average from each column of a training
5 data kernel;

6 storing said column average for later recall, when centering
7 a test data kernel.
8 subtracting a row average form each row of said training data
9 kernel.
1 74. (original) The apparatus of claim 73, said computerized
2 storage, processing and programming for centering said kernel
3 further comprising computerized storage, processing and
4 programming for:
5 adding said stored column average to each column of said
6 test data kernel;
7 for each row, calculating an average of said test data
8 kernel; and
9 subtracting said row average from each horizontal entry of
10 said test data kernel.